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The performance of angel-backed companies[☆]

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ABSTRACT

We provide empirical evidence of the post-investment performance and survivorship profile of angel-backed companies, filling a long-standing gap within the entrepreneurial finance literature. Using a unique database of 111 angel-backed companies that received angel investments between 2008 and 2012 and at least 3 years of post-investment financial data, we develop an innovative performance metric and show that the performance and the probability of survival of investee companies are positively affected by the presence of angel syndicates and the hands-on involvement of business angels, while they are negatively related to the intensity of angel monitoring and the time structure of equity provision. Our results are robust to several endogeneity tests and provide insights on the multifaceted contributions of angel investors to the performance and survival of new ventures.

1. Introduction

Market data at both the US and European levels (US ACA, 2016; Kraemer-Eis et al., 2016; OECD, 2016; Invest Europe, 2017; EBAN, 2017) provide evidence of the growing and significant relevance of Business Angels (BAs) as a main provider of capital to startup companies. BAs have filled the so-called "funding gap" existing between the demand and supply of early-stage equity capital, thus promoting entrepreneurship and economic growth (Mason and Harrison, 2000; Sohl, 2012; Capizzi, 2015). Despite their economic impact, to date, little is known about the performance of corporate investments backed by business angels. This lack of knowledge is comparable to the status of venture capital research prior to the seminal Sahlman (1990) study.

One major factor affecting the quality of the research is the availability of data given the opaqueness of the market and the generally narrow representativeness of survey-based samples (Harrison and Mason, 2008; Capizzi, 2015; Lerner et al., 2016). Additionally, performance studies are further limited by the severe lack of data on private companies in most countries. As a result, contributions investigating the performance of angel-backed companies primarily rely on anecdotal or case-based evidence (Hellman et al., 2013; Kerr et al., 2014; Mason et al., 2016). Thus, it is difficult to find empirical confirmation for some emerging trends in the informal venture capital markets as well as in business angels' investment process (Carpentier and Suret, 2015; Landström and Mason, 2016; Lerner et al., 2016; Harrison and Mason, 2017; Bonini et al., 2018). As for the former, the rising relevance of the phenomena of syndicated angel investments alongside the professionalization and growth all over the world of Business Angel Networks (BAN) do constitute a strong motivation for investigating their possible impact on target companies' performance. As for the latter, reference is made to peculiar angel investment practices, when compared to venture capitalists' ones, in terms of capital infusion, contractual provisioning, monitoring mechanisms and post-investment involvement.

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In this paper, we fill this research gap by relying on a unique database containing qualitative and quantitative information on 690 deals made by 380 business angels on roughly firms, during the period 2008–2012. Matching deals with survivorship and financial performance information up to 3 years after the investment, we obtain a sample of 111 angel-backed companies invested in between 2008 and 2012, on which we perform a comprehensive set of post-investment analyses.

Differently from a previous paper focusing on the determinants of BAs' investment decisions (Bonini et al., 2018), our main unit of analysis is the investee company, which we relate to specific BAs' traits, investment style and background to identify the angel investment mix of monetary and non-monetary contributions that ultimately positively affects the value creation potential of the target venture itself. This is a particularly relevant research question in the light of the conflicting empirical findings about the sources of added value provided by institutional investors and business angels in particular to their target companies (Hellman and Puri, 2002; Dimov and Shepherd, 2005; Hsu, 2006; Sørensen, 2007; Colombo and Grilli, 2010; Chemmanur et al., 2011; Croce et al., 2013).

A critical methodological issue implied by our research program is the selection of an accurate set of metrics to measure performance. The extant literature looking at the impact of venture capitalists on the performance of portfolio companies generally adopts as measures of performance either measures based on financial dimensions such as turnover, market share, and capital assets (Brav and Gompers, 1997; Davila et al., 2003; Engel and Keilbach, 2007; Puri and Zarutskie, 2012) or operating performance dimensions as innovation (Hellman and Puri, 2000; Kortum and Lerner, 2001; Engel, 2002), employment growth (Bertoni et al., 2011; Grilli and Murtinu, 2014) and productivity (Chemmanur et al., 2011; Croce et al., 2013; Croce and Martí, 2016). Alternatively, a significant stream of contributions models positive performance as a dummy variable taking the value of one if the VC exits through IPOs or acquisitions (Black and Gilson, 1998; Manigart et al., 2002; Cumming and Johan, 2013; Johan and Zhang, 2016). However, on the one hand, angel-backed companies are generally pre-revenue, and their financial accounts are often limitedly informative, up to the point that companies can shut down without having generated any sale or having capitalized significant assets. On the other hand, market data on angel-backed companies show that only for a few of them does the investment cycle end with an IPO or an acquisition. The limited literature on the performance of angel-backed companies has adopted very heterogeneous metrics and measurement methodologies. Kerr et al. (2014) developed three different sets of measures: first, they built two binary indicators for survival and success (survival after 4 years from the funding event; successful exit through IPO or acquisition); second, they employed three outcome variables for growth (employment, patents, website traffic); finally, similarly to Collewaert et al. (2010) and Werth and Boeert (2013), they treated the capability of an angel-backed company to raise subsequent venture financing as a performance measure. Alemany and Villanueva (2015) investigated the relationship between the selection criteria adopted by angel investors and the subsequent performance of angel-backed ventures as measured by their sales. Cumming and Zhang (2018) chose as a proxy for the performance of angel investments their successful exits through IPOs or acquisitions. Recently, Levratto et al. (2017) analyzed the impact of BAs on firm growth, as measured by the rate of growth in sales, employment and tangible capital assets.

In this paper, we first show that traditional performance measures – namely, firm size and turnover – have very low predictive power and that the frequency of successful exits through IPOs or M&As is essentially zero in the three years after the investment, thus preventing the use of exit-based metrics. We address this methodological problem by developing an original proxy ("*Performance Index*") for the performance and the probability of subsequent survival of investee companies. The basic idea behind our measurement procedure is that it takes time for a small company receiving an equity injection to (i) deploy the operating investments outlined in the fundraising process, (ii) adjust the business model and company operations, and (iii) start experiencing cash inflows, earnings and increase in the equity capital base. As a consequence, a common growth path following an equity capital injection implies some years of zero or low revenues, negative profits and equity capital erosion, followed by an increase in turnover depending on the beginning of the operations, which could lead to an increase in earnings, cash flows and dividends, possibly implying a future round of financing and the beginning of a further growth path. This pattern may also imply transitory periods of limited, null or negative net asset value before reverting to both positive growth and a sustainable business model. Growing or dying seems to be a crucial node whose major determinants could depend on some causal relationships observed in the investment period and be tied to specific angel investment practices.

Following this line of reasoning, our *Performance Index* is designed as an ordinal variable that can assume five different values associated with five different, measurable company outcomes, capturing differences across the sample on the quality of the funded ventures, based on different combinations of revenues, asset value and income. By breaking down our sample according to the percentile distribution in each class of the performance index and focusing just on the "border" companies, we found further confirmation for discriminating power of our performance metric.

Since we observe each venture in a time span from $t=0$, which is the year when the BA's investment occurred, to $t=3$, each firm can change its status one or more times during the observation period. Therefore, the *Performance Index* is structured as a panel variable that dynamically captures changes in the quality profile of angel-backed companies. Interestingly, our indicator serves also as a proxy of the probability of survival because it is reasonable to assume that successful ventures should experience a higher probability of survival over time than ventures obtaining lower scores. Conversely, we would expect ventures showing negative scores to be future candidates for failure in the subsequent time period.

Our results show that the performance and the probability of survivorship of investee companies are positively affected by the presence of angel syndicates and by the hands-on involvement of business angels, while they are negatively affected by the monitoring effort, especially for less experienced angels. Furthermore, the angel-specific practice of fragmenting the provision of equity investment has a negative impact on the financial performance and the subsequent probability of survivorship. In a set of robustness tests, we control for the death or survivorship of the sample ventures after the observation period, and we support the predictive properties of our measure, the *Performance Index*.

Given the possible presence of several sources of endogeneity, we perform different sets of control tests aimed at minimizing these serious concerns. We begin by using several clustering and fixed-effects strategies; second, absent a specific test for categorical regression models, we adopt a control function method to address possible reverse causality issues; third, we build a control sample of non angel-backed companies and run our model over the untreated companies showing our treated companies are not endogenously better performing than the untreated ones; we conclude by looking at a dynamic version of the performance index to address possible simultaneity issues in our results. Our results hold and support our main conclusions.

The remainder of the paper is structured as follows: the second section presents the hypotheses development; sample data and variables selected for the empirical analysis are discussed in the third section, together with descriptive statistics about the selected angel-backed companies; in the fourth section, we outline the empirical methodology and present the results of the econometric analysis; in the fifth section we provide evidence for the robustness tests run as well as for the predictive power of our performance index; in the last section, we present the concluding remarks and suggestions for future research.

2. Hypotheses development

One major trend observed over time in the market for informal venture capital is the emergence of co-investments made by groups of angels, which have led to a transformation of the investment practices formerly adopted by "solo" angel investors (Paul and Whittam, 2010; Gregson et al., 2013; Mason et al., 2016; Bonini et al., 2018). Co-investments could be made through different degrees of angel syndicates, ranging from structured BANs to semi-informal business angel groups (so-called BAGs) or to informal "club deals" made up on a spot basis just to undertake a single investment opportunity (Lahti and Keinonen, 2016).

By co-investing in a given deal, BAs can enjoy the opportunity to better diversify their investment portfolio and to share the information and know-how of other more experienced angels. While in a previous contribution Bonini et al. (2018) found evidence of a positive relationship between capital invested by BAs and co-investments, consistent with prior work on venture capital and private equity (Lerner, 1994; Brander et al., 2002; Cumming and Walz, 2010; Tian, 2011) in this paper we focus on the effect co-investing generates on angel-backed companies. In fact, a company being funded by a syndicate of angels can leverage on a wider set of monetary and non-monetary contributions than that might be available from a solo angel, thus increasing both its growth potential and its future probability of survival.[1] A higher number of angels simultaneously investing means the possibility to immediately start the business with a higher size scale, market potential and an increased probability to get access to subsequent rounds of financing over time. A further monetary contribution for the angel-backed company comes considering that investors can share the burden of the normally high costs of due diligence, contracting and monitoring required to minimize the adverse selection and moral hazard issues as well as the high agency costs implicit in so informationally opaque an equity investment. Additionally, the non-monetary benefits are higher, in that the funded venture can enjoy multiple sources of coaching and mentoring and take advantage from each BA's industrial knowledge, previous entrepreneurial and management experience, and relationship networks. It is to be highlighted that our arguments are consistent with a resource-based approach applied to entrepreneurial finance (Wright et al., 1998; Van Osnabrugge, 2000; Sørheim, 2003; Wiltbank, 2005; Bonnet and Wirtz, 2012; Werth and Boeert, 2013; Bammens and Collewaert, 2014), whose major implication is the relevant similarities of BAs' and entrepreneurs' cognitive processes. Furthermore, according to Penrose (1959), the kind of contribution and growth opportunity a firm can gain from a given investor is also related to the specific personal experience and learning process of the latter, who is path dependent; therefore, experiences and learning processes differ by investor and, in a context of imperfect markets, may constitute significant drivers of future companies' performance.

This means that the magnitude of an angel syndicate, as measured by the number of co-investors in a given deal, implies a higher quality selection process and a more effective post-investment involvement than those of the 'solo' angels, because of the possibility to leverage on wider experience, knowledge and social capital. Syndicates included in our dataset are exclusively composed by angels arguably sharing common traits, preferences and investment practices. Some recent contributions (Cumming and Walz, 2010; Cumming et al., 2018) found negative effects of syndication on the capability of the funded companies to successfully obtain subsequent financing rounds. However, these results are obtained looking at "mixed" syndicates where angels and structured venture capital investors co-invest in the same deals. The heterogeneity in the type of co-investors undermines the use of the size of the syndicate as the main metric, something that doesn't apply to our sample.

We therefore formulate our first research hypothesis.

H1. *The performance of angel-backed companies is positively affected by the number of co-investors joining a given deal.*

As previously noted, a growing trend significantly transforming the angel market is the emergence of business angel associations. In particular, by affiliating to a given BAN, angel investors can be offered a wide range of opportunities, first among them, the possibility to benefit from a higher quality deal flow. Other contributions come from the information and knowledge-sharing effects taking place inside the community. BAN managers (also known as "gatekeepers") organize periodic training meetings and pitching events aimed at stimulating the interaction between angel investors and entrepreneurs looking for funding (Aernoudt et al., 2007; Ibrahim, 2008; Paul and Whittam, 2010; Brush et al., 2012; Mason et al., 2016). Some angel networks developed own internal academies who arrange focused training and education initiatives targeted to both their own affiliates or to potential entrepreneurs (Josè et al., 2005). In this context, the possibility for inexperienced angels to get access to the human capital of experienced angels inside the BAN is a further valuable opportunity that could subsequently increase their capability to contribute to the value creation process of the investee companies (Shane, 2000). In addition, the quality of the post-involvement contribution given to the angel-backed venture is enhanced by BAN membership, which gives the possibility to finetune and optimize BAs' decision-making styles according to their specific investment behavior in a trust-based environment, ultimately increasing the probability of the company to raise additional growth capital (Wiltbank et al., 2009; Fili et al., 2013; Bonnet et al., 2013; Bammens and Collewaert, 2014).

Such developments in BANs structure and operations have significantly increased the networks role that policymakers, supranational funding institutions and regulators attribute them in boosting and monitoring the startup ecosystems, thus further strengthening the opportunities they provide to entrepreneurs and member angel investors (Aernoudt et al., 2007; Mason, 2009; Collewaert et al., 2010; Christensen, 2011; Harrison, 2017; Kraemer-Eis et al., 2017).

Overall, these arguments suggest a parallel with major findings in the literature dealing with social capital (Coleman, 1988; Granovetter, 1992) when applied to venture capital (Hsu, 2004; Burt, 2005; Dimov and Shepherd, 2005; Hochberg et al., 2007; Hopp, 2010; Alexy et al., 2012): a strong social network of business angels may generate significant valuable opportunities for business angels themselves by granting them access to superior information about startups and their possible growth paths within their reference competitive environment.

[1] We are aware from venture capital literature (Colombo and Grilli, 2010; Croce et al., 2013; Grilli and Murtinu, 2014; Proksch et al., 2017) it is possible to further investigate the determinants of the performance of investee companies by disentangling the selection effect from the funding effect and the non-monetary value adding contribution. Though our research program – and the associated dataset and methodological framework – doesn't allow to pursue such an understanding dealing with business angel investments, we address this as a promising area for future research.

Unfortunately, given the structure of the available dataset, we cannot build and use some traditionally adopted measures for estimating an angel's embeddedness in a social network, such as the size, strength, centrality, specialization and diversification of connections inside a given BAN. However, we reckon that joining a BAN could suggest a willingness to build a social network and take benefit of its opportunities in terms of both human and social capital.

We accordingly formulate our second research hypothesis.

H2. *The performance of angel-backed companies is positively affected by the membership of BAs in a given BAN.*

One fundamental disciplining and monitoring mechanism in venture capital is "stage financing", an investment practice consisting in fractioning the capital infusion in multiple subsequent rounds of financing – also called follow-on investments. In this respect, venture capitalists exploit the option to differ their equity contributions over time, conditional on the venture reaching some target milestones, typically related to financial profitability (size or revenue goals) or technological or scientific achievements (Sahlman, 1990; Gompers, 1995; Bergemann and Hege, 1998; Gompers and Lerner, 2001; Tian, 2011). However, such a mechanism generally implies relatively long time periods – mostly on a plurennial basis – between two financing rounds, and each round is typically provided to the investee as a single capital contribution.

Differentiating from the formal venture capital industry practices, the investment process of business angels is often not completed all at once in a single investment round but is fractioned into two or more cash outs and deferred within a time period of up to 12 months. In other cases, the equity infusion process can be fragmented into more than two monetary contributions in a three-year time period. Such an investment practice depends on several possible explanations, one of them being a matter of liquidity of an angel's financial wealth: it could take some time for the BA – who invests as an individual subject a share of his own personal wealth – to make available from his investment portfolio the liquid assets required to run a single equity capital injection all at once at the signing of the deal ($t = 0$), thus financially constraining the operations and investments of the angel-backed companies. Second, it could be a soft and informal risk management mechanism undertaken by less experienced angels aimed at generating further information about the entrepreneur and the venture prior to increasing their involvement in the firm. A third possible explanation could address the degree of involvement of the BA in the funded venture: BAs desiring to play an active role in the firm would develop a kind of empathy toward the entrepreneurial project, ultimately giving them the incentives to increase their investment in the company beyond what they would have offered had the investment not followed a deferred equity infusion pattern.

However, the kind of companies we are investigating are capital constrained due to their significantly high intrinsic riskiness and cannot finance their investment needs through debt capital or other sources of financing facilities. Thus, the only other financing alternative beyond the initial monetary infusion made by the founders (plus possibly the family and friends tranche) is constituted by the intervention of the angel investors. Deferring their equity infusion over time could affect the nature, scale and time pattern of SMEs' investments as well as the sustainability of their business and revenue model, possibly leading to delayed or compromised cash flow generation. In contrast, investing 100% of the committed capital at $t = 0$ could be proof of a high-quality entrepreneur-investor relationship, where trust, information disclosure and mutual recognition of each other's contribution – monetary and non-monetary – play a major role, ultimately positively affecting firm's future performance.

This leads to the following research hypothesis:

H3. *The performance of angel-backed companies is negatively affected by a temporally deferred equity infusion pattern: fractioning the committed equity provision decreases the performance of the investee companies.*

Though in the literature dealing with informal venture capital research on the post-investment involvement is mainly based on case studies and anecdotal evidence (Ardichvili et al., 2002; Politis, 2008; Macht and Robinson, 2009; Fili and Grünberg, 2016), it is commonly accepted BAs can contribute to their investee companies beyond their capital investment in several different ways, such as mentoring the entrepreneur and company managers, expanding networking and business opportunities, finetuning the governance and the internal control systems.

Bonnet and Wirtz (2012) and Goldfarb et al. (2014), consistent with a cognitive approach to entrepreneurial finance, argue that this behavior is driven by the similarities in personal traits between entrepreneurs and BAs.

Differently from the controversial findings from the venture capital industry, the impact of business angels involvement on portfolio companies is generally found to be positive. Madill et al. (2005) found a positive relationship between the non-monetary contributions provided by the business angels and the possibility to raise subsequent financing from venture capitalists by the investee firms. Chua and Wu (2012) showed that post-investment involvement – and, more in detail, mentoring, rather than monitoring – positively impact business angels' return on their investments. Landstrom and Mason (2016) confirm and extend the previous results showing that BAs' "hands-on" involvement in company operations can meaningfully add value to the target venture. Despite this evidence it is not uncommon to observe BAs adopting a "hands-off" approach more typical of purely financial investors (Benjiamin and Margulis, 2000; Mason and Harrison, 2002; Wiltbank et al., 2006; Bonini et al., 2018). Such behavior, implying a silent participation in the company life and operations as well as a low deal of the above mentioned non monetary contributions provided by the "hands-on" active investors, should be associated with lower performance especially for BAs with a limited potential of both human and social capital in that neither co-invest with other active BAs nor join a BAN (Bonini et al., 2018).

We accordingly formulate our fourth research hypothesis.

H4. *The performance of angel-backed companies is positively affected by BAs' active involvement over the three-year observed time period.*

One major issue in investing in small, risky, and informationally opaque unlisted companies is the possibility of setting up appropriate monitoring mechanisms to reduce the incentives for opportunistic behavior by the entrepreneur and/or the management team of the funded venture.

The finance literature has extensively investigated the effectiveness of a wide number of contingent contracts and financing mechanisms implemented by venture capital organizations to decrease asymmetric information and moral hazard problems (Sahlman, 1990; Triantis, 2001; Kaplan and Stromberg, 2003; Gompers and Lerner, 2004; Wong et al., 2009; Puri and Zarutskie, 2012; Cumming and Johan, 2013; Chemmanur et al., 2014).

In the case of angel investing, however, many contributions have highlighted the low frequency of such "hard monitoring" provisions due to their excessive design and implementation costs for relatively smaller equity investments. In such cases, a possible substitute is represented by "soft" monitoring mechanisms such as geographical proximity, BAs' knowledge of the industry, experience gained from previous investments and, most importantly, interactions with entrepreneurs (Van Osnabrugge, 2000; Kelly and Hay, 2003; Wilbank and Boecker, 2007; Ibrahim, 2008; Wong et al., 2009; Goldfarb et al., 2014; Bonini and Capizzi, 2017). Several important contributions however, have strongly highlighted the importance of the "nexus of trust" in the angel/entrepreneur relationship. In particular, Declercq and Sapienza (2006), Strätling et al. (2012), and Zacharakis et al. (2010) in the context of venture capital, Chua and Wu (2012) and Bammens and Collewaert (2014) focusing on angel investing, have shown that a tightening of the degree of soft monitoring over the investee companies could damage the trust-based relationship between the founder and the angel investor, negatively impacting on the mutual perception on each other's contribution to the venture, possibly worsening the future company performance. Following these contributions, we build a variable labeled "*Soft-Monitoring*" (described in the following section) capturing the ex-ante degree of information opacity of a proposed deal and formulate the following research hypothesis:

H5. *The performance of angel-backed companies is negatively affected by BAs' soft monitoring.*

3. Sample data and variables

Our data are obtained from sequential surveys administered by the Italian Business Angels Network Association (IBAN) to its associates and other unaffiliated BAs beginning in 2007. The IBAN is the national trade association for angels and angel groups/networks. A full description of the survey procedure is reported in Bonini et al. (2018).[2]

To investigate how the BA investment decisions affect firm performance and survival, following prior contributions (Collewaert et al., 2010; Kerr et al., 2014; Alemany and Villanueva, 2015), we choose to rely upon available data for each firm for an observation period of at least four years. In particular, we observe each venture in a timespan from $t=0$, which is the year when the BA's investment occurred, to $t=3$. We therefore select deals in the 2008–2012 IBAN surveys to maximize the availability of financial statements 3 years after the investment for all sample firms that survived

From a starting sample of 695 deals, we had to exclude a significant number of observations because the name of the target company was not specified or was specified incorrectly, preventing an unequivocal identification. This reduces the sample to 302 start-ups. We then performed a manual search of two external data sources, Orbis and Lexis/Nexis, to collect data from financial statements and any relevant information on acquisitions and initial public offerings involving the selected ventures. This procedure returned complete data for 111 firms, whereas for the other 191 firms, it was not possible to obtain a series of three consecutive annual financial statements. Table 1 reports the details of the filtering process.

The sample coverage is fairly uniform across the years, with the exception of 2008, which exhibits a significantly lower number of deals. This figure is likely due to two different factors. First, 2008 is the inception year for IBAN surveys. Accordingly, it is not unlikely that the procedure was refined in the following years. Second, because of the eruption of the financial crisis, the second half of 2008 experienced a record low number of new firms created. We address this possible concern by introducing year fixed-effects in all regressions that should absorb a significant portion of such heterogeneity. Additionally, we run a robustness check on three subsamples obtained by restricting the year of the BA's investment. The results are qualitatively unchanged.

Table 1
Sampling procedure.
This table presents details on the filtering process leading to the final sample. From a starting sample of 695 deals (Column 1), we exclude observations where the name of the target company was not specified or incorrectly specified preventing an unequivocal identification (Column 2). We then keep companies for which financial statements and any relevant information on acquisitions and initial public offerings is available on Orbis and Lexis/Nexis (Column 3).

Year of the BA investment	(1)	Number of fully identified deals (2)	Panel firms (3)	(2)/(1) (4)	(3)/(2) (5)
2008	92	10	2	11%	20%
2009	145	59	12	41%	20%
2010	137	86	27	63%	31%
2011	159	74	23	47%	31%
2012	162	73	47	45%	64%
Total	695	302	111	43%	37%

In Table 2, Panel A, we show the industry distribution of the final sample data.

Looking at the industry distribution of investments, deals are spread out across several industries, with a not surprising dominance of "traditional" sectors for new ventures, such as ICT, electronics and biotech, which collectively attract approximately half of the aggregate investments. Interestingly, 13% of the amount invested is directed at cleantech-related ventures, consistent with a rising global trend of this activity (Lerner et al., 2016; Mason et al., 2016; Kraemer-Eis et al., 2016).

We report summary statistics on revenues, earnings and net asset value in Panel B and for the timespan from $t=0$ to $t=3$ in Panel C. Considering the revenues, we can observe that many ventures have already started to sell their products or services at $t=0$, while 13% of firms show zero revenues. It is interesting that 23% of firms show zero revenues one year after the BA investment, and 8% of them are still inactive three years later, confirming that BAs are patient investors, available to wait for years before the business starts its operations and begins generating revenues and cash flows. Looking at the net asset value, we observe that the average assets of approximately 240,000 euro and maximum assets of 1.2 million euro fit the profile of newly funded companies. However, it is worth noting that several firms show a negative net asset value already in the BA's investment year and that their incidence grows in the subsequent years, consistent with the peculiar revenues and cash flow generating patterns of companies in the early stages of their life cycles that make such companies the peculiar asset class for BAs and venture capitalists (Gompers, 1995; Gompers and Lerner, 2001; Mason and Harrison, 2002, Landström and Mason, 2016). Not surprisingly, about the 75% of the participated firms show negative net income in the year when the deal was made. Nevertheless, the incidence of ventures with negative earnings also remains high in the subsequent years, overcoming the 70% of the sample in $t=3$, which confirms the substantial level of risk of investments in early-stage companies.

Measuring performance is a debated issue in the extant entrepreneurial finance literature. In fact, traditional measures based on financial variables are almost invariably inadequate to measure performance, and if applied, the cross-section is very dispersed and noisy.[3] Several contributions have tried to tackle this problem by either employing some non-financial metrics such as "exits" (Cumming and Zhang, 2018) or the joint analysis of different traditional

[2] Each survey is completed in a four-step process: at the beginning of January, IBAN forwards the survey's website link to its associates and other known BAs. By the first week of March, the data are collected (step 1). Non-responsive BAs are contacted by email and phone to solicit survey completion (step 2), while an IBAN team reviews the data to identify incomplete, wrong or unverifiable answers (step 3), which are further checked through direct follow-up calls (step 4). This process is a fairly common survey technique called sequential mixed mode (Snjikers et al., 2013), and evidence shows that it significantly improves the response rate (De Leeuw, 2005 and Dillman et al., 2009).

[3] Collewaert et al. (2010) and Vanacker et al. (2013) used the ROA as a proxy for performance over two different samples of Belgium angel-backed companies reporting, however, controversial evidence about the quality of such measure for the post-investment value adding contribution provided by BAs.

Table 2
Sample descriptive statistics.
This table presents details on sample firms characteristics. Panel A presents industry distribution data; Panel B presents summary statistics for the 3 main financial indicators: revenues, Net Income and Net Assets, by post-investment year.

PANEL A- Industry distribution		
	Number of firms	%
Biotech	19	17.1
Cleantech	15	13.5
Commerce and distribution	10	9.0
Electronics	17	15.3
Information and Communications Technology (ICT)	20	18.0
Media & Entertainment	10	9.0
Other sectors	20	18.0
Total	111	100.00

PANEL B - Firms financials by year (euro)					
	Mean	Std. Dev.	Median	Freq. <=0	Freq. > 0
Revenues					
t0	474,269	1,454,245	67,461	13%	88%
t1	456,071	1,284,199	57,906	23%	77%
t2	508,855	1,206,058	81,879	17%	83%
t3	760,174	1,669,722	149,080	8%	92%
Net Assets					
t0	240,952	515,146	67,811	6%	94%
t1	214,796	591,338	66,799	9%	91%
t2	222,973	772,393	58,663	17%	83%
t3	240,801	977,414	82,902	18%	82%
Net Income					
t0	−86,233	261,515	−13,381	75%	25%
t1	−117,388	294,332	−33,576	80%	20%
t2	−147,404	271,817	−34,875	72%	28%
t3	−150,152	304,543	−25,577	71%	29%

metrics (Macht and Robinson, 2009; Levratto et al., 2017). Both approaches have strengths and weaknesses. On the one hand, while exits are undoubtedly an objective measure of success, the number of observed exits is unconditionally small, and when applied to small samples, the measure may not exhibit sufficient variation in the left-hand side variable to allow meaningful inferences. This is, unfortunately, the case in our sample, where we have evidence of only a handful of events that could possibly qualify as exits in the Cumming and Zhang (2018) sense. On the other hand, Levratto et al. (2017) approach of alternatively employing several ratios comes at a cost of returning conflicting results that may indicate success under one metric and failure under another.

In the light of these constraints, we propose expanding the multiple metrics approach by developing an ordinal index based on commonly accepted measures. Our Performance Index (P.I.), whose underlying rationale has been developed in the previous Section 1 of the paper, assumes five different ordinal scores:

- 2 when revenues, net asset value and net income are positive;
- 1 when revenues and net asset value are positive but net income is negative;
- 0 when revenues are positive but net asset value and net income are negative;
- −1 when revenues are zero and net income is negative but net asset value is positive;
- −2 when revenues are zero and net income and net asset value are negative.

While it is computationally possible to derive additional alternative combinations of outcomes, we think the 5 selected ones identify combinations of financial results that are consistent with the 5 performance scenarios commonly outlined in financial accounting literature (Anthony and Ramesh, 1992; Black, 1998; Fama and French, 2000; Nissim and Penman, 2001; Omrani and Karami, 2010; Dickinson, 2011) and practice (Damodaran, 2015; Fabozzi et al., 2015).[4]

Since the collection and analysis of firms' annual reports allow us to observe the changes in the value of the accounting items over time, each firm can change its status one or more times during the observation period. Thus, our Performance Index is a panel variable.

Table 3, Panel A presents the detailed frequency distribution of ordinal values in the observation period from $t=0$ to $t=3$ showing that observations are fairly well distributed over time within the 5 classes of the P.I..

The strength of the P.I. is given by the joint assessment of its three main components. In fact, taken individually, revenues, net assets and net income may yield to substantially diverging conclusions. In Panel B we highlight this by showing summary statistics of the constituents of the P.I. for contiguous companies across classes. In particular, we compute within-class distribution quartiles of the P.I. constituents and classify companies in top/bottom quartiles if at least two out of three financial indicators fall in the top/bottom quartile. For example, within each class, the top/bottom quartile group includes those companies with two out of three indicators in the top 25% of the within-class distribution. We then compare the characteristics of companies ranked in the borders of each contiguous class of the P.I., so to check for the discriminating power of our performance metric. In column (3) of Table 3, Panel B, we present differences in means and significance tests for border companies across each P.I. class. Results indicate that looking at individual factors only would yield substantially different, and often conflicting, classifications of companies. For example, the worst companies of the P.I. class 1 exhibit higher revenues but lower asset value than the best companies of the lower

[4] In order to provide further support to the 5 selected categories, in the section devoted to the robustness checks we provide supplemental tests of the accuracy and predictive power of the P.I..

Table 3
Performance-Index composition and distribution.
This table reports summary statistics for the variable PERFORMANCE-INDEX. The variable is designed as an ordinal variable which can assume five different values based on different combinations of revenues, asset value and income. We compute the variable on annual basis over a time span from $t = 0$, which is the year when the BA's investment occurred, to $t = 3$. The last row reports the number of firms in each year for which the financial statement is missing. PANEL B reports the mean values for the variables Revenues, Net Asset and Net Income. PANEL C presents the mean value of Revenues, Net Income and Net Assets for the firms in the contiguous border classes (top/bottom 25% distribution) of the perfomance index. Column (3) tests for the inequality of the means between the contiguous borders and presents the differences between the means. *, ** and *** denote statistical significance at 10%, 5% and 1% levels respectively.

PANEL A - Performance index composition

Description	Ordinal Value	Distribution of ordinal value in T0 to T3				
		T0	T1	T2	T3	Total by value
Net asset value, Net income and Revenues are positive	2	20	20	30	21	91
Net asset value and revenues are positive but net income is negative	1	47	41	50	41	179
Both net asset value and net income are negative but revenues are positive	0	3	8	9	20	40
Net asset value is positive revenues are equal to zero and net income is negative	−1	8	31	12	3	54
Both net asset value and net income are negative and revenues are equal to zero	−2	2	1	10	3	16
Number Firms without financial statement in t_n		31	10	0	23	64
Observation by year		111	111	111	111	444

PANEL B - Revenues, Net Assets and Net Income mean values by Performance Index level (euro)

Ordinal Value	Revenues (1)	Net Assets (2)	Net Income (3)
2	1,338,900	324,379	60,261
1	363,723	382,008	−189,016
0	214,584	−705,509	−250,940
−1	0	245,320	−117,444
−2	0	−283,167	−281,719

PANEL C - Comparison between contiguous borders of different classes of the performance index (euro)

		Bottom border of the higher class (1)	Top border of the lower class (2)	Higher class border vs Lower class border (3)
Lower 25% of the performance index = 2 class	Revenues	126,025	1,092,697	−966,672***
vs	Net Assets	12,136	897,035	−884,899***
Upper 25% of the performance index = 1 class	Net Income	498	−70,963	71,461***
Lower 25% of the performance index = 1 class	Revenues	6,107	245,760	−239,974***
vs	Net Assets	36,437	−38,122	74,559**
Upper 25% of the performance index = 0 class	Net Income	−49,608	−7,407	−42,201
Lower 25% of the performance index = 0 class	Revenues	64,038	0	64,037
vs	Net Assets	−1,585,178	756,714	−2,341,891**
Upper 25% of the performance index = −1 class	Net Income	−522,003	−22,466	−499,536**
Lower 25% of the performance index = −1 class	Revenues	0	0	0
vs	Net Assets	119,399	−12,551	131,950**
Upper 25% of the performance index = −2 class	Net Income	−328,317	−33,479	−294,838**

class. Similar patterns can be observed in many other instances, thus clearly indicating that measuring performance of young, start-up companies through a single metric is inevitably prone to severe classification problems and that a more comprehensive index as the one proposed can alleviate such problems. In Section 5.3 we present further support to this by looking at the ability of the P.I. to predict survivorship compared with single factors.

In Table 4, we present descriptive statistics of the set of the explanatory and control variables. A full correlation matrix is reported in Table A1.[5]

We test the first research hypothesis through the variable *Co-investors*, which should be positively related to our Performance Index. This variable assumes values from a minimum of zero to a maximum of 15 investors. Considering the median and the mean values, however, we observe that the majority of angel-backed companies have fewer than five associated investors.

In our second research hypothesis, we test the impact of BAN affiliation on performance with the dummy *BAN-membership*. In the presence of co-investors, the variable assumes the value one if at least one BA participating in the deal shows a BAN affiliation.

Our third research hypothesis addresses the kind of monetary injection chosen by BAs, which could be realized either with a single investment round at $t = 0$ or according to a deferred temporal pattern through fragmented equity injections, though in a short time frame (usually less than one year). To generate a measure of this anomalous and original investment practice, we build the dummy variable *Equity_infusion_pattern*, which assumes the value of one for ventures that have received two separate capital injections by the same BA. Table 5 presents descriptive statistics for the sample conditional on the value assumed by the *Equity_infusion_pattern* variable. The statistics do not support the possible arguments related to BAs' wealth and experience, while the high share of BAs playing an active role in the business project could constitute first descriptive evidence supporting the BA's "empathic behavior argument" toward the entrepreneur. It is also interesting to observe that all the ventures receiving two separate capital injections already produce positive revenues at $t = 0$ and have positive net asset value but negative net income.

With the dummy *Active involvement*, we control for the willingness of the BA to play an active role post his investment with the aim of providing valuable non-monetary contributions to the

[5] Caution needs to be employed when dealing with a categorical or binomial dependent variable, as the interpretation of correlation of such types of dependent variables is substantially different than that of continuous dependent variables.

Table 4
Independent variables: descriptive statistics.
This table reports descriptive statistics for the main independent variables and a set of angel-specific and firm-specific controls found in the extant literature to be correlated with start-up firm performance.

Variables	Description	Obs.	Median	Mean	St. Dev.	Min	Max	Dummy = 1 percentage
Co-investors	Numbero of co-investors	111	1	3.766	5.1	0	15	
BAN_Membership	Dummy = 1 if at least one BA owns to the Italian BA Network (IBAN)	110						53%
Equity_infusion_pattern	Dummy = 1 in presence of different investment rounds	111						5%
Active Involvement	Dummy = 1 if the BA has made managerial contributions to the invested firm	111						68%
Soft-Monitoring	Ordinal variable ranging from 1 to 5	98	3	2.95	1.18	1	5	
Angel-specific controls								
Age-BA	Average age of the BA/BAs participating to each investment	99	49	48.17	9.56	30	70	
Experience-BA	Number of past deals of angel financing. In presence of co-investing, it is the number of deals of the most expert BA.	99	7	6.69	3.96	0	12	
Share-BA	Share of BAs' participation in the firm	111	0.08	0.16	0.20	0.01	1	
Firm-specific controls								
Age-Firm	Age of the firm at the time of the BA investment	107	1	3.13	4.86	0	27	
Equity	Firm's equity in euro	78	156,872	366,000	511,221	2,501	2,525,291	
Foreign	Dummy = 1 for foreign firms	107						7%
Pre-Investment Revenues	Dummy = 1 if revenue was greater than zero when the BAs' investment occurred	105						66%

Table 5
Descriptive statistics by type of equity infusion pattern.
In this table we present summary statistics of selected angel and firm characteristics conditional on the pattern of equity provision modeled as the dummy variable Equity_infusion_pattern, which assumes the value of one for those ventures that have received an investment by one BA in multiple installments.

	One Capital injection	Multiple capital injections
Experience		
Median	7	9.5
Mean	6.54	8.833
Min	0	3
Max	12	12
Managerial contribution (freq)	0.67	0.83
	Frequencies at $t=0$	
Revenues > 0	0.64	1
Revenues = 0	0.36	0
Earnings < = 0	0.8	1
Earnings > 0	0.2	0
Net asset value < = 0	0.05	0
Net asset value > 0	0.95	1
Observations	105	6

funded venture. Although in the following empirical analysis the survey question was primarily framed as a binary response item, to differentiate between “active” and “passive” angel investors, the questionnaires provided interesting additional information, allowing to understand more in detail the nature of the BAs' involvement. Respondents who elaborated on how they expected to be involved with the venture converged over a few contributions: sharing financial knowledge (32.9%), sharing industrial experience (27.6%), sharing marketing knowledge (22.4%) and offering strategic and management advice (75.0%). Unfortunately, detailed responses were not sufficient to allow adequate coding of the different response items so to include them in econometric analyses; therefore we opted for a dummy variable specification.

To test our final research hypothesis, we built an ordinal variable (*Soft-Monitoring*) assuming a value from 1 to 5, depending on the frequency of the visits a BA makes to its portfolio companies (Bonini et al., 2018), where 1 means very limited involvement (no or few company visits) and 5 means high involvement (a constant presence in the firm). We want to investigate whether an increase in the monitoring effort is a sufficient and effective value contributing tool available to BAs or rather a behavior negatively affecting the performance of the angel-backed company because of its impact on the trust and the quality of the relationship with the entrepreneurial team, especially in a context lacking the more formal hard monitoring mechanisms that are contractual-based and typically implemented in venture capital deals (Cumming, 2008).

Following the extant literature, we add to our tests a vector of controls capturing BAs' characteristics. A first series of controls is angel-specific and accounts for age, experience – as measured by the number of past deals – and the share of the equity stake assumed by the BA (Mason and Harrison, 2000; Van Osnabrugge, 2000; Shane, 2000; Paul et al., 2007; Sudek et al., 2008; Macht, 2011; Collewaert and Manigart, 2016). We expect more profitable ventures to be positively affected by older and more experienced BAs. Furthermore, the higher the control in the funded venture is (either considering the share of the solo angel or considering the cumulative equity stake of the angel syndicate joining a given deal), the higher the commitment of the BAs to make more and more effective monetary and non-monetary contributions, thus increasing both performance and probability of survival of the angel-backed company. A second series of controls is firm-specific and addresses the company size – as measured by its monetary equity base – its age and stage in the life cycle – measured by the positive value of revenues before the investment ($t=0$) – and its location (domestic or foreign-based). Consistent with the extant literature, we expect that the performance of angel-backed companies is positively affected by their size, age and pre-investment revenue capacity (Wiltbank et al., 2006; Vanacker et al., 2013; Alemany and Villanueva, 2015; Levratto et al., 2017) and negatively affected by their location (Sudek et al., 2008). Finally, we complete the model by considering time and industry fixed effects for their expected impact on angel-backed companies' performance (Mason and Harrison, 2002; Wiltbank and Boeker, 2007; Werth and Boeert, 2013; Kerr et al., 2014; DeGennaro and Dwyer, 2014; Capizzi, 2015; Alemany and Villanueva, 2015; Levratto et al., 2017).

4. Methodology and results

4.1. The determinants of the performance of angel-backed companies

We begin our econometric analysis by performing a set of ordinal logistics (Ologit) regressions analysis on our 111 treated firms observed over a four-year time period, where $t=0$ is the year of the BA's investment. The dependent variable is the five-stage ordinal variable Performance Index that we test through the following categorical model:

$$y_i = BX + \Phi FirmControls + \Xi AngelControls + \tau + \theta + \epsilon$$

where

y_i = the ordinal response of the *Performance Index* (−2; −1, 0, 1, 2).

X = is a vector of the following explanatory variables: *Co-investors, BAN_membership, Equity_infusion_pattern, Active Involvement, Soft-Monitoring*.

FirmControls = is a vector of the following controls: *Age-Firm, Equity, Foreign, Pre-investment Revenues*.

AngelControls = is a vector of the following controls: *Age-BA, Experience-BA, Share-BA*.

τ *and* θ are time and industry fixed effects, respectively.

When dealing with variables characterized by multiple ordered responses, the previous model is truly

$$\Pr\left(y_n < k\right) = \frac{\exp\left(X_n \beta_k\right)}{1 + \sum_k^K \exp\left(X_n \beta_k\right)}$$

Accordingly, the regressions return cut-points that capture the crossing point of the latent variable.

In all models, standard errors are computed as Huber-White robust standard errors to allow asymptotically unbiased results, without having to assume homoscedasticity and normality of the random error terms. Given that we also introduce time and industry dummies for the most likely cluster levels, we believe that this approach provides consistent estimations.

Model results, presented in Table 6 (columns (1)–(3)), show that a higher number of co-investors positively affects the performance of angel-backed companies, thus confirming our first research hypothesis. By getting access to equity capital raised by a syndicate of BAs, a company can also leverage on a wide set of non-monetary contributions, leading to an increase in its performance and probability of survival.

The independent variable is statistically significant in each model specification. Different from our expectation, the affiliation to a BAN does not seem to affect the probability of success of angel-backed firms. However, this could be due to the intrinsic features of our survey-based dataset, which does not allow the possibility to account for the qualitative differences in the various forms of potentially existing angel associations.

One direction for future research, hence, could be the analysis of the differences in the operations and revenue models as well as in the quality of the services and contributions that different kind of BANs offer to their members (Kerr et al., 2014; Landström and Mason, 2016; Mason et al., 2016).

The dummy *Equity_infusion_pattern* is negative and strongly significant in all model specifications. The interpretation is that fragmenting an agreed capital contribution into multiple injections significantly reduces the performance. It is worth recalling that this behavior is crucially different from staging in that it pertains to the delayed provision of an agreed financial investment. Investing 100% of the committed capital in $t=0$ is proof of a high-quality entrepreneur-investor relationship, where trust, information disclosure and mutual recognition of each other's contribution – monetary and non-monetary – play a major role, ultimately affecting the firm's future performance.

Turning to the results of our analysis, we cannot find support for our fourth research hypothesis, as BAs' *Active Involvement* does not appear to be statistically correlated with the performance of angel-backed companies. Differently, *Soft-Monitoring* turns out negative and significant in fully specified equations, thus lending support to hypothesis 5.

Looking at the impact of the control variables, model outcomes show that BAs' experience, in terms of number of past deals, has a positive influence on future firm performance, as does BAs' age, thus confirming the results of the previously cited empirical analyses performed over different geographical samples. Similarly, achieving good performances in a four-year time period is easier for firms with low capital intensity than for business projects that require greater capital injections.

As expected, the positive sign of the variable *Pre-Investment Revenues* confirms that the firms that at $t=0$ already sell their products or services are more likely to perform well in the future than those that still have to develop a viable monetization strategy. The variable *Pre-Investment Revenues,* however, is likely correlated with firm age and contributes to the definition of the ranking of the *Performance Index* in $t=0$. For these reasons, we run the main specification by alternatively dropping the age and pre-investment revenue variables. The results presented in models (4) and (5) are essentially unchanged. Given that we run ordered logistic regressions, standard intercepts are replaced by cut points, which essentially represent the points where the latent response variable changes. Absolute values clearly change across specifications but importantly the distance between cuts (say cut1 –cut2) is relatively similar across specifications supporting the robustness of the estimations.

These results suggest that the contribution to company performance by BAs is more effective when it is made by teams of co-investors that include BAs with consolidated experience and capabilities to access better quality deal flow and selection processes.

4.2. Economic interpretation of the ordinal logistic regressions

Ordinal logistic models are typically less straightforward to interpret than standard OLS models. In fact, the classical approach of relating the economic effect of a change in the variable of interest on the dependent variable would lead to misleading estimates, as categorical models are non-linear. To provide more intuition of the economic effects of the estimates presented in Panel A, in Table 6, Panel B, we present predicted probabilities and estimates of the changes in probabilities obtained from model 3.

Quadrants I to III plot the predicted probability of observing a positive ($y_i=2$) or negative ($y_i<=-1$) outcome of the Performance Index conditional on the three explanatory variables with significant estimates. Quadrant I shows that the number of co-investors substantially reduces the predicted probability of a negative outcome, which for large groups of co-investors approaches zero (theoretically). While this does not obviously imply that to avoid negative performance one should simply add investors to a venture, it does underscore the importance of the post-investment value adding contributions that investors bring to a portfolio company, most of all the non monetary ones, such as mentoring and networking. Similarly, positive performances are substantially more likely in the presence of multiple co-investors, with a predicted probability that ranges from an unconditional 15% (1 investor) to almost 35%. Quadrant II can be interpreted similarly and indicates that a fragmented capital provision increases the predicted probability of observing a negative performance from approximately 10% to approximately 50%. Similarly, the probability of observing a positive performance decreases by more than 60%, from more than 20% to less than 10%. In line with the relatively small parameter estimated in the regressions, the predicted probability graph in Quadrant III suggests that an intense interaction-based monitoring is associated with a higher (lower) likelihood of observing negative (positive) performance. Interestingly, this variable is associated with the highest decrease in the probability of observing the highest levels of performance, suggesting that a more effective driver of the performance of a new venture, rather than soft monitoring,

Table 6a
PANEL A - Ordinal regressions results.
The table reports results of a battery of ordinal logit panel regressions of the performance of angel-backed firms. The dependent variable, PERFORMANCE-INDEX, is a five-stage ordinal variable taking five possible values: −2 when revenues are zero and net income and net asset value are negative; −1 when revenues are zero and net income is negative but net asset value is positive; 0 when revenues are positive but net asset value and net income are negative; +1 when revenues and net asset value are positive but net income is negative; +2 when revenues, net asset value and net income are positive. Column (1) reports are a reduced model with fixed-effect. Column (2) adds to the previous model two more explanatory variables. Column (3) introduces angel-specific and firm-specific controls. In columns (4),(5) we replicate estimations dropping alternatively the highly correlated variables Pre Investment-Revenues - that captures whether the firm had revenues before the investment - and Age-firm. Huber-White heteroscedasticity consistent standard errors are reported in parentheses. ***, **, and * denote significance at the1%, 5% and 10% level respectively.

	(1)	(2)	(3)	(4)	(5)
Co-investors	0.057**	0.057**	0.064**	0.057*	0.063**
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
BAN_Membership	0.306	0.181	0.109	0.303	0.225
	(0.24)	(0.32)	(0.38)	(0.38)	(0.37)
Equity_infusion_pattern	−1.638***	−1.584***	−1.787***	−1.824***	−1.971***
	(0.38)	(0.41)	(0.45)	(0.46)	(0.44)
Active Involvement		0.151	0.624*	0.439	0.479
		(0.27)	(0.32)	(0.31)	(0.31)
Soft-Monitoring		−0.09	−0.398***	−0.317**	−0.316***
		(0.11)	(0.12)	(0.13)	(0.12)
Angel-specific controls					
Age-BA			0.009	0.025**	0.007
			(0.01)	(0.01)	(0.01)
Experience-BA			0.066*	0.075**	0.079**
			(0.04)	(0.04)	(0.03)
Share-BA			0.365***	0.207*	0.297**
			(0.14)	(0.12)	(0.13)
Firm-specific controls					
Age-Firm			−0.377***	−0.162	
			(0.14)	(0.12)	
Equity			−0.294***	−0.225***	−0.291***
			(0.09)	(0.09)	(0.09)
Foreign			0.126	0.581	0.254
			(0.60)	(0.55)	(0.56)
Pre-Investment Revenues			1.308***		0.822**
			(0.43)		(0.38)
Time-effect	Yes	Yes	Yes	Yes	Yes
Industry-FE	Yes	Yes	Yes	Yes	Yes
cut 1	−3.890***	−4.046***	−7.603***	−6.331***	−7.129***
cut 2	−2.109***	−2.405***	−5.793***	−4.569***	−5.354***
cut 3	−1.433***	−1.666***	−5.304***	−4.093***	−4.874***
cut 4	0.828***	0.721	−2.625**	−1.449	−2.235*
Pseudo R^2	0.06	0.07	0.10	0.09	0.09
N	377	336	303	306	303

is a trust-based active involvement, not nurtured by increasingly frequent company visit.

In Quadrant IV, we present marginal effects as a change in the predicted probabilities for all 5 explanatory variables when the variable of interest moves from its minimum value to its maximum value. Not surprisingly, changes are small for the variable that returned insignificant. By contrast, the magnitude of change for the 3 significant variables is large and economically meaningful.

5. Robustness checks

5.1. Sub-sampling by year, age, revenues, size of investment and monitoring

As a first robustness check, we perform a set of alternative regression analyses on several subsamples to check for possible sample biases. The results are presented in Table 7.

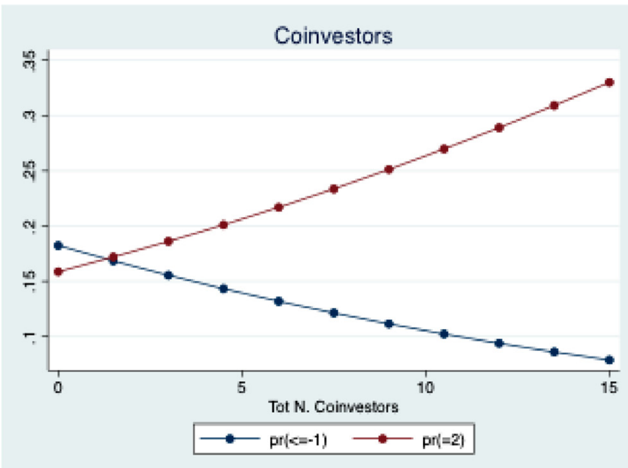
BAs' contribution could be more effective in achieving profitability and survival over time in ventures that are more opaque and potentially more innovative than those with an *ex-ante* higher observable quality. To this end, we run our analysis isolating homogeneous groups of firms in terms of investment year, age, ex ante quality (as measured by their pre-investment revenue capacity), capital intensity (as measured by their equity endowment) and angel-reported monitoring intensity.

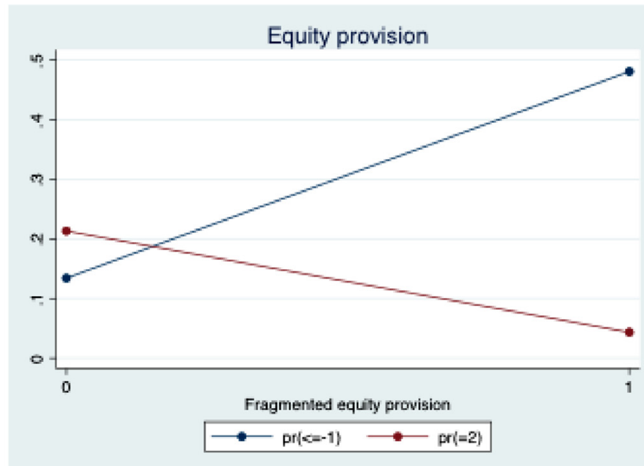
First, we differentiate the whole sample in three different subsamples by progressively excluding firms receiving investments on or after 2009, 2010 and 2011. The results confirm that the selected explanatory variables *Co-investors, Equity_infusion pattern* and *Soft-Monitoring* are significantly related to firm performance and survival independently of the investment year and therefore independently of the kind of angel-investment cycle, which may have exogenously changed after the great financial crisis. Looking at the subsample of firms invested in after 2011, the parameter for the variables *BAN_Membership* is weakly significant and positive, as expected from hypothesis 2. We interpret this result as suggestive of the steep growth and structural changes observed in angel organizations in the second half of 2000 (Gregson et al., 2013; Mason et al., 2016), that have been progressively improving the quality and effectiveness of their operations.

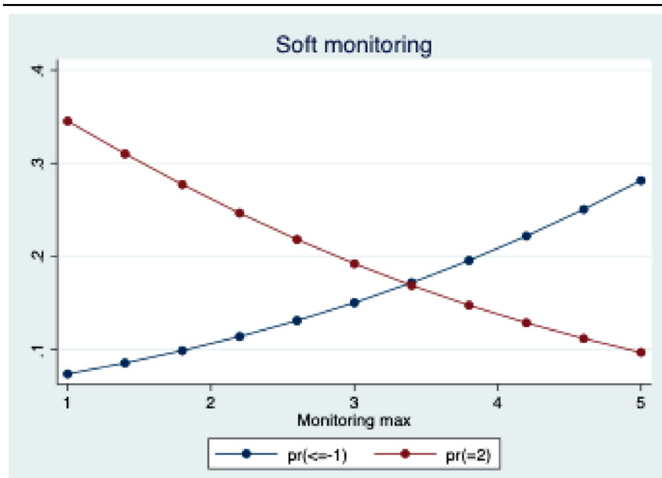
Second, we create two subsamples on the basis of firm age: the first subsample, named "*start-up*", includes firms founded two years or less prior to the investment. Older firms are coded as "*pre-existing*". While the results for *Soft-Monitoring* are independent on firm age, we find that the positive effect of *Co-investors* and the negative effect of the fragmented capital provision on firm performance can be generally attributed to investments in older ventures. Together, this result indicates that the success of investee companies that are no longer in the startup phase is crucially dependent on the timely provision of capital and the joint non-monetary contribution of multiple investors.

Third, we split the sample into two groups of firms considering the presence of revenues in the investment year. The results

Table 6b
PANEL B - Marginal Effects and Predicted Probabilities.
This table reports predicted probabilities for changes in the three significant explanatory variables in model (3), Table 6-PanelA (quadrants I-III) and marginal effects for all 5 explanatory variables (quadrant IV). Probabilities are plotted for the highest (+2) and two-lowest (<=−1) values of the Performance Index. Marginal effects are reported for changes in the relavant explanatory variable from its Minimum to its Maximum value.







Change from Minimum to Maximum value in variable:	Change in predicted probability	
	P.I.= -2	P.I.= 2
Co-investors	-2,50%	17,29%
BAN_ Membership	-0,29%	1,70%
Equity_ infusion_ pattern	10,78%	-16,99%
Active Involvement	-1,96%	8,90%
Soft-Monitoring	2,75%	-19,61%

are qualitatively similar to those observed in the previous sample breakdown and consistent with research hypotheses 4 and 5. Furthermore, we find that in ventures with revenues at the time of investment, the *Active Involvement* variable is positively related to the *Performance Index*, implying that it is most of the all the hands-on approach, rather than the Soft-Monitoring, that represents the value-creating contribution business angels can offer to their investee companies in a framework of mutually transparent trust-based and pre-determined investment relationships. An unexpected result is the negative and rather strongly significant ($p < 0.03$) impact on firm performance given by *BAN_Membership* for firms with no revenues. In the light of the relatively recent history of BANs as semi-formal organizations, this result may suggest that BANs themselves experience a "learning curve" in investment selection skills. In unreported regressions, we have further segmented the sample by restricting the analysis to subgroups of firms invested in during different periods. The previous results significantly weaken, and the results for firms invested in after 2010 disappear, thus confirming our interpretation. However, this result is far from conclusive, and future extensions are needed to shed light on the economic effects on performance of business angel networks.

Fourth, we consider the capital intensity of the business, dividing the sample into two subsamples on the basis of the median value of the variable Equity. While confirming in both subsamples the significance and the causal relationships observed for the variables *Equity_infusion_pattern* and *Soft-Monitoring*, the variable *Co-investors* appears statistically significant only for larger sized investee companies, thus implying that there is a minimum investment size required to make the presence of an angel syndicate beneficial. In fact, transaction and coordination costs generated by the presence of a multitude of investors may exceed the monetary and non-monetary contributions provided by co-investors.

5.2. Endogeneity

Corporate finance studies are unfortunately likely to be biased due to several sources of endogeneity. Our analysis is similarly not immune from these problems, and while we believe that the survey data collection process has been designed to minimize these concerns, more formal testing is needed.

Table 7
Sub-sample regressions.
The table reports results of a battery of ordinal logit panel regressions of the performance of angel-backed firms on different sub-samples. The dependent variable, PERFORMANCE-INDEX, is a five-stage ordinal variable taking five possible values: −2 when revenues are zero and net income and net asset value are negative; −1 when revenues are zero and net income is negative but net asset value is positive; 0 when revenues are positive but net asset value and net income are negative; +1 when revenues and net asset value are positive but net income is negative; +2 when revenues, net asset value and net income are positive. Investment year regression exclude progressively firms that received investment on or after 2009, 2010 and 2011. Firm-age regressions identify as start-up those firms with an age at the time of the investment of two years or less. Firm revenues regression partition the sample between firms that have zero or non-zero revenues. Firm equity regressions are run separately on firms that exhibit above/below median equity at the time of investment. For table compactness, regression cut points are unreported. Huber-White heteroscedasticity consistent standard errors are reported in parentheses. ***, **, and * denote significance at the1%, 5% and 10% level respectively.

	Investment year			Firm-age		Firm-Revenues at $t=0$		Firm Equity	
	>2009	>2010	>2011	Start-up	Preexisting	No Revenues	Revenues	=< Median value	> Median value
Co-investors	0.062**	0.075***	0.131***	−0.034	0.119*	−0.085	0.112***	0.027	0.132***
	(0.03)	(0.03)	(0.03)	(0.04)	(0.07)	(0.06)	(0.03)	(0.05)	(0.04)
BAN_Membership	0.191	0.302	1.272*	−0.242	1.386	−1.441**	0.454	0.162	0.668
	(0.39)	(0.49)	(0.67)	(0.43)	(0.85)	(0.63)	(0.49)	(0.45)	(0.68)
Equity_infusion_pattern	−1.844***	−2.467***	−3.346***	−0.525	−2.997***		−2.615***	−2.258*	−3.118***
	(0.45)	(0.57)	(0.74)	(0.83)	(0.78)		(0.56)	(1.17)	(0.76)
Active Involvement	0.645**	0.319	−0.485	−0.061	0.923	−0.194	0.838**	0.471	1.206**
	(0.32)	(0.43)	(0.64)	(0.44)	(0.83)	(0.58)	(0.43)	(0.46)	(0.55)
Soft-Monitoring	−0.413***	−0.355*	−0.851***	−0.314**	−1.132***	−0.208	−0.586***	−0.728***	−0.550**
	(0.12)	(0.20)	(0.32)	(0.14)	(0.43)	(0.24)	(0.17)	(0.24)	(0.23)
Angel-specific controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	YES
Firm specific controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	YES
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	YES
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	YES
Pseudo R^2	0.11	0.14	0.23	0.08	0.24	0.17	0.15	0.11	0.19
N	301	220	140	204	99	87	216	155	162

Given the time and industry distribution of our sample, a first problem addresses the existence of unobserved characteristics in the sample. We have addressed this problem by the tests presented in Tables 6 A-B and 7 with alternative sets of fixed-effects and clustering levels that may partially address these concerns. Unreported results are qualitatively unchanged. However, several other sources of bias might be at play, particularly reverse causality in the two explanatory variables, *Equity_infusion_pattern* and *Co-investors*.

5.2.1. Reverse causality and control function regression

The *Equity_infusion_pattern* variable might potentially be affected by reverse causality, in that investors may choose to provide capital in a fragmented fashion only to firms that have an inherently higher degree of risk. This concern is partially mitigated by the evidence found in our previous tests indicating that the behavior is particularly negative and significant for pre-existing and revenue generating companies that are not the lowest performing ventures within the whole sample. However, more careful handling is needed to convincingly minimize these concerns.

In the absence of outright tests applicable to categorical dependent variable regressions, an alternative solution that is partially satisfactory is given by applying a control function regression approach (Wooldridge, 2002; Windmejier and Santos Silva, 1997) that involves regressing the possibly endogenous variable over a plausibly exogenous instrument, estimating the fitted values, running the ordinal logistic regressions again and adding the predicted term. The absence of significance for the residual term is considered a reliable test of the exogeneity of the variable of interest.

The instrument for the possibly endogenous variable is the dummy Low_Wealth, which assumes the value 1 if at least one of the angels participating in the deal belongs to the lowest wealth bracket of the IBAN survey and zero otherwise. We believe that the instrument passes the exclusion restriction test, as it is unlikely that a personal wealth high enough to qualify the individual as a business angel but lower than that of another investor may have an impact on the ex-ante quality of the deal. Table 8 presents the results of this test for the variable Equity infusion pattern.

In column 1, we instrument the possibly endogenous variable through a logit model and estimate the fitted values. In the second stage, we estimate the original categorical model adding the predicted values from the logit regression (Equity infusion pattern (fitted)) to the list of regressors. The results indicate that the fitted values are insignificant, while the supposedly endogenous regressor is still significant.

This result significantly mitigates the concerns about the endogeneity of the original variable. However, we reckon that although this approach is considered acceptable in the literature it still presents some shortcomings and is certainly less conclusive than other more traditional approaches.

A similar, although weaker, causality concern might be raised for the variable *Co-investors*. Unfortunately, no valid instrument is available to replicate the approach implemented above. However, a number of arguments can be put forth to address this possible issue. For this argument to be valid, we would need to observe a significantly different distribution of high/low performance deals conditional on the level of co-investment. We addressed this idea by inspecting the composition of the angel syndicates in our sample. The data indicate that we have an almost perfectly balanced presence of co-investors in both successful and unsuccessful cases. In fact, we have evidence of the presence of angel syndicates in more than 50% of the dead firms, although the difference is not statistically significant. Additionally, in a non-negligible 10% of the cases, we find evidence of the same group of angels being involved in both successful companies and defaults.

While not fully conclusive, this evidence provides a solid argument against reverse causality for the variable *Co-investors*. Interestingly, we notice that this same evidence may hint at the existence of a possible "matching" problem in the early-stage financing market. The significant informational opaqueness may in fact translate also in a suboptimal access to investment opportunities and funding for investors and entrepreneurs respectively. This intuition seems consistent with anecdotal evidence but is completely absent in the literature. We envision this as a possible area of further research.

Table 8
Control function regressions.
In this table we present results of a control function methodoloy test for the endogeneity of the independent variable "Equity infusion pattern". Given that the dependent variable is ordinal and regressions are categorical, we present results of a control function approach where we first instrument the possibly endogenous variable through a logit model and we estimate the fitted values (Wooldridge, 2002; Windmejier and Santos Silva, 1997). In the second stage we estimate the original categorical model adding the predicted values from the logit regression. The instrument for the possibly endogenous variable is the dummy Low_Wealth which assumes value 1 if at least one of the angels participating to the deal belongs to the lowest wealth bracket of the IBAN survey and zero otherwise. Huber-White heteroscedasticity consistent standard errors are reported in parentheses. ***, **, and * denote significance at the1%, 5% and 10% level respectively.

	Instrument = Low_Wealth	
	Step 1 Y = Equity Infusion Pattern	Step 2 Y = Performance Index
Low_Wealth	3.188**	
	(1.25)	
Co-investors		0.112***
		(0.03)
BAN_Membership		0.418
		(0.54)
Equity_infusion_pattern		−2.775***
		−0.581
Equity_infusion_pattern (fitted)		0.115
		(0.14)
Active Involvement		0.677
		(0.45)
Soft-Monitoring		−0.555***
		(0.17)
Age-BA	0.592**	−0.004
	(0.24)	(−0.47)
Experience-BA	0.736**	0.022
	(0.29)	(1.04)
Share-BA	−0.228	0.180**
	(0.30)	(2.29)
Age-Firm	0.347**	−0.318***
	(0.14)	(−3.21)
Equity	1.153***	−0.095**
	(0.26)	(−2.14)
Foreign	3.013***	−0.062
	(1.00)	(−0.17)
Pre-Investment Revenues		
Time-effect	No	Yes
Industry-FE	No	Yes
cut 1		−7.603***
cut 2		−5.793***
cut 3		−5.304***
cut 4		−2.625**
Pseudo R^2	0.53	0.17
Observations	212	209

5.2.2. Selection bias

A possible concern in our analysis is that angel-backed companies are intrinsically better performers than their peers. Our analysis focuses on how some investor characteristics impact the performance of invested companies, thus selectivity is relatively less severe a concern than in other contexts. However, we try and address this issue by identifying a plausibly matching sample of non angel-backed start-ups and then comparing their pre-investment financial characteristics with those of our sample companies. We identify similar firms by selecting from the Amadeus/Bureau van Dijk database, companies established between 1997 and 2012. We then selected companies in the same industry and size bracket, and with total assets lower than 3.5 million euro in t_0, where t_0 is measured as the foundation year for startups that received angel investment in their first year and the age of the firm at the time of the angel investment for preexisting companies. We obtained a population of roughly 170.000 companies, from whom we randomly selected 120 matching firms with the same proportion of new ventures (65%) vs. preexisting firms (35%) of our angel-backed sample. As a final control, we looked in detail at the ownership structure of the selected companies aimed at excluding the presence of angel or financial investors through a manual inspection on the Italian Register of Enterprises filings. More in detail, consistent with a widely accepted definition of business angels, we identified as business angels investors with minority equity holdings in three or more ventures. We found two companies not passing such exclusion criterion, leading to our final control sample of 118 non angel-backed firms.

We fully reckon this is not a perfect matching exercise but we believe it provides sufficient generality to address the concern of selectivity in our tests that are focused at capturing the effects of angels characteristics on investee firms rather than comparing angel-backed vs. non-angel-backed companies.

Table 9, Panel A presents evidence of the sampling procedure process. Table 9, Panel B and C, offers descriptive statistics for both the treatment and the control sample, allowing to observe the confirmed statistically significant similarity in t0 between the two sample as far as both industry distribution and business fundamentals are concerned. Not surprisingly, the net asset value of the angel-backed companies is higher than that observed for the control sample companies, as a consequence of the funding contribution given by BAs.

Overall, this evidence mitigates the selectivity concern at least with regards to observable factors. Of course, it is fully possible that firms have some unobservable characteristics that dispropor-

Table 9
Control sample descriptive statistics.
This table presents details on control-sample firms characteristics. Panel A presents the sampling procedure. Panel B offers industry distribution data; Panel C compares firms charateristics in t0 between the control sample and the angel backed sample and, in column (3), presents the differences between the means. *, ** and *** denote statistical significance at 10%, 5% and 1% levels respectively.

PANEL A- Sampling procedure

	Population (1)	Total Asset < = 3.5 M € (2)	Selected sectors (3)	Raw control sample (4)	Final control sample (5)
Founding year 2008–2012	339,602	160,872	83,004	78	76
Founding year 1997–2007	591,853	304,208	85,942	42	42
Total	931,455	465,080	168,946	120	118

PANEL B- Industry distribution

	Control sample (1)	Angel backed sample (2)	Control vs angel backed sample (3)
Biotech	10.2	17.1	−6.9
Cleantech	13.6	13.5	0.1
Commerce and distribution	10.2	9.0	1.2
Electronics	6.8	15.3	−8.5**
Information and Communications Technology (ICT)	14.4	18.0	−3.6
Media & Entertainment	12.7	9.0	3.7
Other sectors	32.2	18.0	14.18**
Total	100.00	100.00	

PANEL C - Firms characteristics in t_0

	Control sample (1)	Angel backed sample (2)	Control vs angel backed sample (3)
Firm age	2.3	3.1	−0.8
Total asset	681,047	1,023,601	−342,554
Revenues	556,131	474,269	81,862
Net asset value	136,682	240,952	−104,270*
Net income	11,892	−86,233	98,124**

tionately attract investors and somewhat affect our sample selection.

5.2.3. Simultaneity and performance index dynamics

An additional source of endogeneity might be given by simultaneity. We address this issue by adopting a modified version of our Performance Index that, rather than looking at levels, estimates the effects of our explanatory variables on changes in the P.I. one or three years after the investment. We model changes in the Performance Index as a trinomial variable that takes the value of −1 if the P.I. drops by one or more notches over the next year or the next 3 years; 0 if the Performance Index is unchanged; and +1 if the P.I. increases by one or more notches over the next year or the next 3 years. The results are reported in Table 10.

While the estimates are weakened by the substantially reduced sample size, especially on the 3-year window, the results are aligned in sign with those of the main regressions and largely maintain significance across the response categories, thus supporting our main conclusions.

5.3. The predictive power of the performance index

As previously discussed, our three-year Performance Index could be used as an effective proxy for estimating the probability of survival of angel-backed firms. To this end, we created a dummy variable, "*Survival*", assuming the value one for those firms that have survived (i.e., have not been liquidated or filed for bankruptcy) four years after the initial investment, or zero otherwise. We gathered this information from the Orbis and Lexis/Nexis databases, augmented by manual Google and LinkedIn company profile searches. We then run a set of logistic regressions on the dependent variable Survival against our main explanatory variable, Performance Index. Following Levratto et al. (2017), we run alternative specifications using Total Assets and Total Revenues as predictors.

Table 10
Performance index dynamics.
The table reports results of tests of the effets of the main explanatory variable on the dynamic of the performance index. Regressions are multinomial logistic regressions of the 1-year and 3-years changes in performance index. The dependent variable can take value of: −1 if the performance index drops by one or more notches over the next year or the next 3 years; 0 if the performance index is unchanged; +1 if the performance index increases by one or more notches over the next year or the next 3 years. The baseline outcome is 0 (no change). Huber-White heteroscedasticity consistent standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% level respectively.

	1-year change		3-years change	
	−1	1	−1	1
Co-investors	−0.120***	−0.009	−0.186**	−0.012
	(0.05)	(0.05)	(0.09)	(0.06)
BAN_Membership	0.721	0.672	0.179	0.425
	(0.54)	(0.56)	(0.66)	(0.70)
Equity_infusion_pattern	1.930*	1.301	3.017*	−14.963***
	(0.99)	(0.95)	(1.82)	(1.15)
Active Involvement	−0.228	−0.442	−1.079*	−0.867
	(0.58)	(0.51)	(0.62)	(0.73)
Soft-Monitoring	−0.231	−0.375*	−0.369	0.362
	(0.22)	(0.21)	(0.31)	(0.27)
Angel-specific controls	Yes	Yes	No	No
Firm specific controls	Yes	Yes	No	No
Time FE	Yes	Yes	No	No
Industry FE	Yes	Yes	Yes	Yes
Intercept	0.706	1.784	0.525	−2.935**
	(2.18)	(2.19)	(1.03)	(1.28)
Pseudo R^2	0.20		0.25	
N	214		96	

The results in Table 11 PANEL A support the effectiveness of the P.I. as a predictive measure of the probability of survival of an angel-backed firm. Differently, traditional financial measures do

Table 11
Performance measures and survival.
In this table we present results for a set of logistic regression estimating the survival of firms from our main performance measure - Performance Index - and two traditional measures of performance, all measured in t0. The dependent variable is a dummy assuming value one for those firms that have survived (i.e. have not been liquidated or filed for bankruptcy) four-year after the intial investment, or zero otherwise. We alternatively specify the main explanatory variable as follows: Performance Index, Total Assets and Total Revenues. All regressions include Industry Fixed Effects. Huber-White heteroscedasticity consistent standard errors are reported in parentheses. ***, **, and * denote significance at the1%, 5% and 10% level respectively.

PANEL A - SURVIVAL

	(1) Angel-backed Sample	Control Sample	(2) Angel-backed Sample	Control Sample	(3) Angel-backed Sample	Control Sample
Performance-Index	0.623**	0.359*				
	(0.29)	(0.191)				
Total Assets			−0.163	0.038		
			(0.18)	0.141		
Revenues					0.081	0.032
					(0.06)	0.043
Industry-FE	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	0.759	0.682**	3.497	0.557	0.49	0.728
	(0.53)	(0.341)	(2.48)	(1.764)	(0.76)	(0.495)
Pseudo R^2	0.159	0.06	0.131	0.03	0.119	0.04
N	80	114	80	114	80	114

PANEL B - DETERMINANTS OF SURVIVAL

Co-investors	0.234*
	−0.126
BAN_Membership	2.307*
	(1.322)*
Equity_infusion_pattern	−4.561*
	−2.343
Active Involvement	−0.498
	(1.281)
Soft-Monitoring	0.16
	(0.264)
Angel-specific controls	Yes
Firm specific controls	Yes
Time FE	No
Industry FE	Yes
Intercept	−5.384
	(6.382)
Pseudo R^2	0.505
N	66

not appear to have substantial predictive power. Interestingly, we obtain qualitatively similar results when using the control sample which, on one side mitigates selectivity concerns of the main sample and on the other side further support the P.I. rationale. These results are consistent with the arguments we have put forth motivating the development of a more comprehensive measure of performance that can better disentangle the peculiar financial patterns usually observable in young ventures.

In the light of our previous results on the determinants of the P.I., in Panel B, we run a logistic regression with the same set of independent variables used in our main specification (Table 6 A, Model 3). The results confirm the outcome of our base model: Co-investing actually increases the probability of surviving over time, while deferring the equity injection by the BA in subsequent time periods increases the probability of a future company closing down. Additionally, we observe that the probability of close down increases with the firm age. Interesting to highlight, BAN affiliation shows a negative relationship with company failure, suggesting that, at least for the worst performing companies, membership in a given BAN is positively correlated with the survival of angel-backed companies, consistent with research hypothesis 2.

6. Conclusions

In this paper, we provide previously unavailable evidence on the post-investment performance and probability of survival of angel-backed companies conditional on an original set of independent variables related to business angels' investment practices (*Co-investors, BAN_Membership, Equity_infusion pattern, Active Involvement, Soft-Monitoring*). Contributing to the extant literature, we introduce an innovative ordinal metric ("Performance Index") that we use as a dependent variable differentiating companies according to their revenue and profit generation pattern.

We base our research hypotheses on a sample of 111 angel-backed companies extracted from a unique database containing qualitative and quantitative information on 690 deals made by 380 business angels on roughly firms, during the period 2008–2012. Our main results show that the performance and the probability of survivorship of investee companies are positively affected mostly by the presence of syndicates of co-investing angels, indicating their ability to generate a higher quality deal flow and selection process while offering to funded ventures a wider set of non-monetary contributions, crucial to survivorship and future growth.

Looking at the survivorship of companies, we show that our Performance Index offers substantial predictive power, being able to predict survival up to four years after the investment. We also provide evidence that the membership in a given BAN is positively correlated with the survival of angel-backed companies, in particular for the weakest performing companies of the sample, and that equity capital should be provided at once, rather than fragmented in multiple disbursements. We interpret this result as

Table A1
Correlation matrix.

	Performance Index	Co-investors	BAN_Membership	Equity_infusion_pattern	Active Involvement	Soft-Monitoring	Age-BA	Experience-BA	Share-BA	Age-Firm	Equity	Foreign	Pre-Investment Revenues
Performance Index	1												
Co-investors	0.06	1											
BAN_Membership	0.0725	0.186**	1										
Equity_infusion_pattern	−0.121*	0.375***	0.241***	1									
Active Involvement	0.0772	0.053	0.147*	0.0488	1								
Soft-Monitoring	0.0763	−0.0377	0.389***	−0.0337	0.181**	1							
Age-BA	0.00362	0.071	−0.0332	0.155**	−0.154**	−0.201***	1						
Experience-BA	0.207***	0.168**	0.255***	0.215***	0.0344	0.279***	0.045	1					
Share-BA	0.133*	−0.0987	0.283***	0.061	−0.0826	0.366***	−0.084	0.270***	1				
Age-Firm	−0.162**	0.0534	−0.0898	0.172**	−0.0307	−0.378***	0.352***	−0.103	−0.166**	1			
Equity	−0.0353	0.303***	−0.0424	0.241***	0.225***	−0.076	0.0897	0.188**	0.0308	0.162**	1		
Foreign	0.0807	0.211***	0.0326	0.181**	0.141*	−0.0354	−0.160**	0.116*	−0.134*	0.0274	−0.0525	1	
Pre-Investment Revenues	0.109	0.130*	−0.00925	0.159**	−0.0138	−0.0887	0.333***	0.128*	−0.282***	0.500***	0.270***	0.155**	1

follows: the immediate investment of the total committed capital is a signal of a high-quality relationship between the investee company and the angel investors, where the former has been able to fully disclose information about the company and the projected investments, and the BA, thanks to its experience, has been able to provide the required capital together with the right incentives. Finally, BAs' active involvement seems to constitute a value-creating mechanism that is more effective than soft monitoring (based on company visits rather than on the formal contractual provisions set up by venture capitalists) in driving the angel-backed companies to profitability and survival; this is especially true for funded ventures with yet limited revenue capacity at the investment period.

These results indicate that valuable BA investments need to be characterized by a balanced blend of investment practices, networking skills, background experience and investment style. This "angel investment formula" is more effective in generating positive performance than a stand-alone capital contribution.

One consequent policy implication aimed at further boosting the entrepreneurial environment of a given country could be the design of focused financing facility schemes leveraging on the value adding potential of BAs, such as, for example, the creation of public-private angel co-investment funds. Furthermore, it has to be emphasized the opportunity to recognize and incentivize the pivotal role angel networks could play in the startup ecosystem, given their intrinsic potential as mechanisms for sharing among BAs information, experience and knowledge.

Summing up, our results provide the first evidence of the performance of angel-backed companies, overcoming the severe data limitations affecting previous studies. However, several areas may benefit from further analytical improvement. First, more detailed data and longer time series may allow more structured survival analyses such as the Cox proportional hazards model, as in Manigart et al. (2002) and Pommet (2012). Second, the differential impact on the performance of angel groups and networks has only been marginally explored in this study. More evidence is needed to highlight whether and how different association rules, membership and services structures and BAN management practices can affect the survival and performance of new ventures. Third, additional insights may come from the collection of additional variables capturing more granularly angel investment practices such as: BAs previous investment experience, the different personal background of BAs, and the type of securities contracts underwritten when funding a company. We leave these issues as suggestions for future research.

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